2007년도 대한전기학회 하계학술대회 논문집 2007. 7. 18 - 20

개선된 DE 알고리즘을 이용한 전력계통의 경제급전

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An Improved Differential Evolution for Economic Dispatch Problems with Valve-Point Effects

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Abstract – This paper presents an efficient approach for solving the economic dispatch (ED) problems with valve-point effects using differential evolution (DE). A DE, one of the evolutionary algorithms (EAs), is a novel optimization method capable of handling nonlinear, non-differentiable, and nonconvex functions. And an efficient constraints treatment method (CTM) is applied to handle the equality and inequality constraints. The resultant DE-CTM algorithm is very effective in solving the ED problems with nonconvex cost functions. To verify the superiority of the proposed method, a sample ED problem with valve-point effects is tested and its results are compared with those of previous works. The simulation results clearly show that the proposed DE-CTM algorithm outperforms other state-of-the-art algorithms in solving ED problems with valve-point effects.

1. INTRODUCTION

Economic Dispatch (ED) is one of the most important problems in power system operation and planning. The purpose of the ED problem is to determine the optimal combination of power outputs of all generating units so as to meet the required load demand at minimum operating cost while satisfying system equality and inequality constraints. In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques such as lambda-iteration method, gradient-based method, etc. [1]. These mathematical methods require incremental or marginal fuel cost curves which should be monotonically increasing to find global optimal solution. Unfortunately, the input-output characteristics of generating units are inherently highly nonlinear because of prohibited operating zones, valve-point loadings, and multiple effects, etc. Therefore, the practical ED problem is represented as a nonconvex optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Dynamic programming method [2] can solve such types of problems, but it suffers from so-called the curse of dimensionality. Over the last few decades, as an alternative to the conventional mathematical approaches, many salient methods have been developed [3]-[6].

A differential evolution (DE) developed by Storn and Price [7] is a very simple and easy to use evolution strategy, which is significantly faster and robust stochastic global optimizer. In DE, the fitness of an offspring competes one-to-one with that of the corresponding parent. This one-to-one competition, which is different from other evolutionary algorithms (EAs), gives rise to a faster convergence rate. In addition, DE has limited number of parameters, which include mutation factor, crossover rate and population size, in comparison with other competing heuristic optimization methods [8].

The aim of this paper is to present an efficient method for solving the ED problems with nonconvex cost functions using DE-CTM algorithm. The DE is a powerful global optimizer in nonconvex optimization problem. And the constraints treatment method (CTM) is applied so as to effectively handle the equality and inequality constraints. The resultant DE-CTM algorithm is very powerful in solving the nonconvex ED problems.

2. FORMULATION OF ECONOMIC DISPATCH

2.1 Basic ED Formulation

The objective of the ED problem is to minimize the total fuel cost of thermal power plants subjected to the operating constraints of a power system. In general, it can be formulated mathematically with an objective function and two constraints [1].

$$F = \sum_{i=1}^{n} F_i(P_i) \quad (1)$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad (2)$$

where F is the total generation cost, F_i the is cost function of generator i, a_i, b_i, c_i are the cost coefficients of generator i, P_i is the power output of generator i, and n is the number of generators.

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss

$$\sum_{i=1}^{n} P_i = P_D + P_{Loss} \quad (3)$$

where P_D is the total system demand and P_{Loss} is the total line loss. However, the transmission loss is not considered in this paper for simplicity (i.e., $P_{Loss} = 0$).

In addition, generation output of each generator should be laid between minimum and maximum limits. The corresponding inequality constraint for each generator is

$$P_{i,\min} \le P_i \le P_{i,\max} \quad (4)$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum output of generator i, respectively.

2.2 ED Problem Considering Valve-Point Effects

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions. Since the valve point results in the ripples, a cost function contains higher order nonlinearity. Therefore, the equation (2) should be replaced as (5) to consider the valve-point effects. Here, the sinusoidal functions are thus added to the quadratic cost functions as follows:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + |e_i \sin(f_i (P_{i,\min} - P_i))| \quad (5)$$

where e_i and f_i are the cost coefficients of generator i reflecting valve-point effects.

3. DE-CTM ALGORITHM FOR ED PROBLEMS

3.1 Differential Evolution

A DE developed by Storn and Price [7] is a population-based evolutionary computation technique, whose simple yet powerful and straightforward features make it very attractive for resolving the nonsmooth global optimization problems. In DE, the fitness of an offspring competes one-to-one with that of the corresponding parent. This one-to-one competition will give rise to a faster convergence rate than other EAs [8].

Since the decision variables in ED problems are real power outputs, the structure of an individual is composed of a set of elements. Therefore, at generation *G*, individual *i*'s position can be represented as the target vector $X_i^{(G)} = \left(P_{i1}^{(G)}, \cdots, P_{in}^{(G)}\right)$ where n is the number of generators in the ED problem.

1) Initialization: The initial individuals are randomly chosen within their bounds (i.e., $P_{i,\min}$ and $P_{i,\max}$). That is, in the initialization process, a set of individuals is created at random as follows:

$$P_{ij}^{(0)} = P_{j,\min} + r_{ij} \times \left(P_{j,\max} - P_{j,\min}\right) \tag{6}$$

where r_{ij} is a random number between [0,1] for element j of individual i.

2) Mutation: A mutant vector $X'^{(G)}_i$ is generated based on the present individual $X_i^{(G)}$ as follows:

$$X'^{(G)}_i = X_{r1}^{(G)} + MF \times \left(X_{r2}^{(G)} - X_{r3}^{(G)}\right) \tag{7}$$

with random indices $r_1, r_2, r_3 \in [1, NP]$. Note that the randomly chosen integers r_1, r_2, and r_3 are have to be different from each other and from the running index i (i.e., $i \neq r_1 \neq r_2 \neq r_3$), so that NP must be at least four. MF is a real and constant factor, which controls the amplification of the difference between two individuals and is usually taken from the range [0, 1].

3) Crossover: In order to increase the diversity of the population, crossover is introduced. The trial vector $X''^{(G)}_i$ is generated as follows:

$$P''^{(G)}_{ij} = \begin{cases} P'^{(G)}_{ij} & \text{if } r_{ij} \leq CR \\ P_{ij}^{(G)} & \text{otherwise} \end{cases} \tag{8}$$

for j=1,2,…,n. CR is the crossover rate in the range [0,1].

4) Selection: To create the new population in the next generation G+1, the fitness value of the trial vector $X''^{(G)}_i$ is compared with its parent vector $X_i^{(G)}$. If the trial vector $X''^{(G)}_i$ yields a better objective function value than $X_i^{(G)}$, then $X_i^{(G+1)}$ is set to $X''^{(G)}_i$. Otherwise, the target vector $X_i^{(G)}$ is retained.

$$X_i^{(G+1)} = \begin{cases} X''^{(G)}_i & \text{if } F\left(X''^{(G)}_i\right) \leq F\left(X_i^{(G)}\right) \\ X_i^{(G)} & \text{otherwise} \end{cases} \tag{9}$$

5) Stopping Criteria: The proposed algorithm is terminated if the iteration reaches the predefined maximum iteration.

3.2 Constraints Treatment Method

Michalewicz and Schoenauer [9] surveyed and compared several constraint-handling techniques used in evolutionary algorithms (EAs). Penalty functions are the most popular methods in EAs to handle the system constraints due to its simple concept and convenience to implementation. However, these methods have certain weaknesses that the penalty functions tend to be ill-behaved near the boundary of the feasible region when the penalty parameters are large. In this paper, the heuristic-based CTM, which was successfully applied to ED problems in [3], is adopted to handle the equality and inequality constraints effectively.

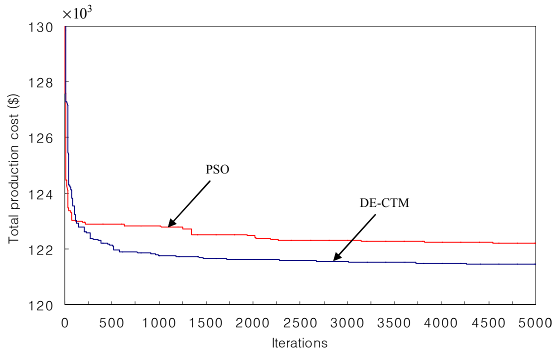
4. CASE STUDY

This system consists of 40 generating units and the input data for 40-generator system are given in [4]. The total demand is set to 10,500MW. Since the performance of DE can depends on its parameters such as population size NP, maximum iteration count $iter_{\max}$, mutation factor MF, and crossover rate CR, it is important to determine the suitable values of parameters. In this numerical test, NP, $iter_{\max}$, MF, and CR are set to 30, 5,000, 1.0, and 0.3, respectively and 100 independent trials are conducted to compare the solution quality and convergence characteristics.

In Table 1, the results obtained by the proposed DE-CTM are compared with those from previous works. Although the acquired best solution from DE-CTM is not guaranteed to be the global solution, the proposed algorithm has shown the superiority to the previous researches in all trials as described in Table 1. And the convergence characteristics of the PSO and the DE-CTM are compared in Fig. 1.

<Table 1> Comparison of Results of Various Methods

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation
IFEP [4]	122,624.35	123,382.00	125740.63	N/A
MPSO [3]	122,252.265	N/A	N/A	N/A
DEC-SQP [5]	121,741.9793	122,295.1278	122,839.2941	386.1809
NPSO-LRS [6]	121,664.4308	122,209.3185	122,9815913	N/A
DE-CTM	**121,433.5005**	**121,459.7590**	**121,500.8648**	**18.0298**



<Fig. 1> Convergence characteristics of PSO and DE-CTM

5. CONCLUSION

This paper presents a new approach for solving the ED problems with nonconvex cost functions using DE-CTM. The proposed DE-CTM algorithm is combined DE as the powerful global optimizer with CTM as the constraint-handling technique. The proposed algorithm has been applied to ED problem considering valve-point effects, and its results have been compared with other state-of-the-art algorithms so as to verify the performance of DE-CTM. The simulation results clearly show that the proposed DE-CTM was indeed capable of obtaining higher quality solution efficiently in the nonconvex economic dispatch problems.

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